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(54) **GENERATING DUAL SEQUENCE INFERENCES USING A NEURAL NETWORK MODEL**

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(Continued)

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G06N 3/04 (2023.01)
G06F 16/2458 (2019.01)

(Continued)

(52) **U.S. Cl.**
CPC ***G06N 3/04*** (2013.01); ***G06F 16/2462*** (2019.01); ***G06F 16/93*** (2019.01); ***G06N 3/006*** (2013.01);

(Continued)

(58) **Field of Classification Search**
CPC G06N 3/08; G06N 5/04; G06N 3/0481; G06N 3/0454; G06N 3/006; G06N 3/04;

(Continued)

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(57) **ABSTRACT**

A computer-implemented method for dual sequence inference using a neural network model includes generating a codependent representation based on a first input representation of a first sequence and a second input representation of a second sequence using an encoder of the neural network model and generating an inference based on the codependent representation using a decoder of the neural network model. The neural network model includes a plurality of model parameters learned according to a machine learning process. The encoder includes a plurality of coattention layers arranged sequentially, each coattention layer being configured to receive a pair of layer input representations and generate one or more summary representations, and an output layer configured to receive the one or more summary representations from a last layer among the plurality of coattention layers and generate the codependent representation.

20 Claims, 8 Drawing Sheets

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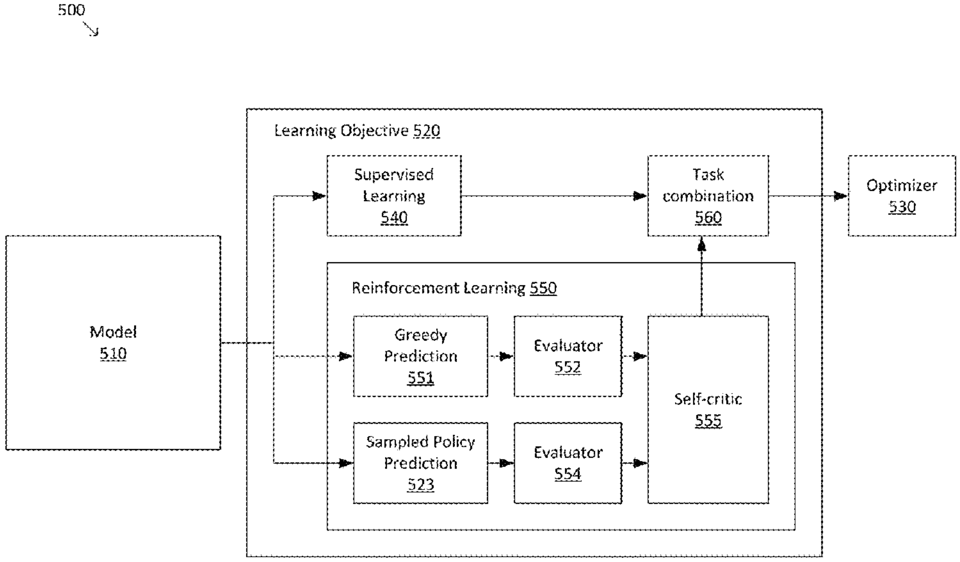

Related U.S. Application Data

(60) Provisional application No. 62/578,380, filed on Oct. 27, 2017.

(51) **Int. Cl.**

G06F 16/93	(2019.01)
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G06N 3/044	(2023.01)
G06N 3/045	(2023.01)
G06N 3/08	(2023.01)
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(58) **Field of Classification Search**
CPC .. G06N 3/0464; G06N 3/0475; G06N 3/0495; G06N 3/0499; G06N 3/045; G06N 3/048; G06F 16/93; G06F 16/2464
See application file for complete search history.

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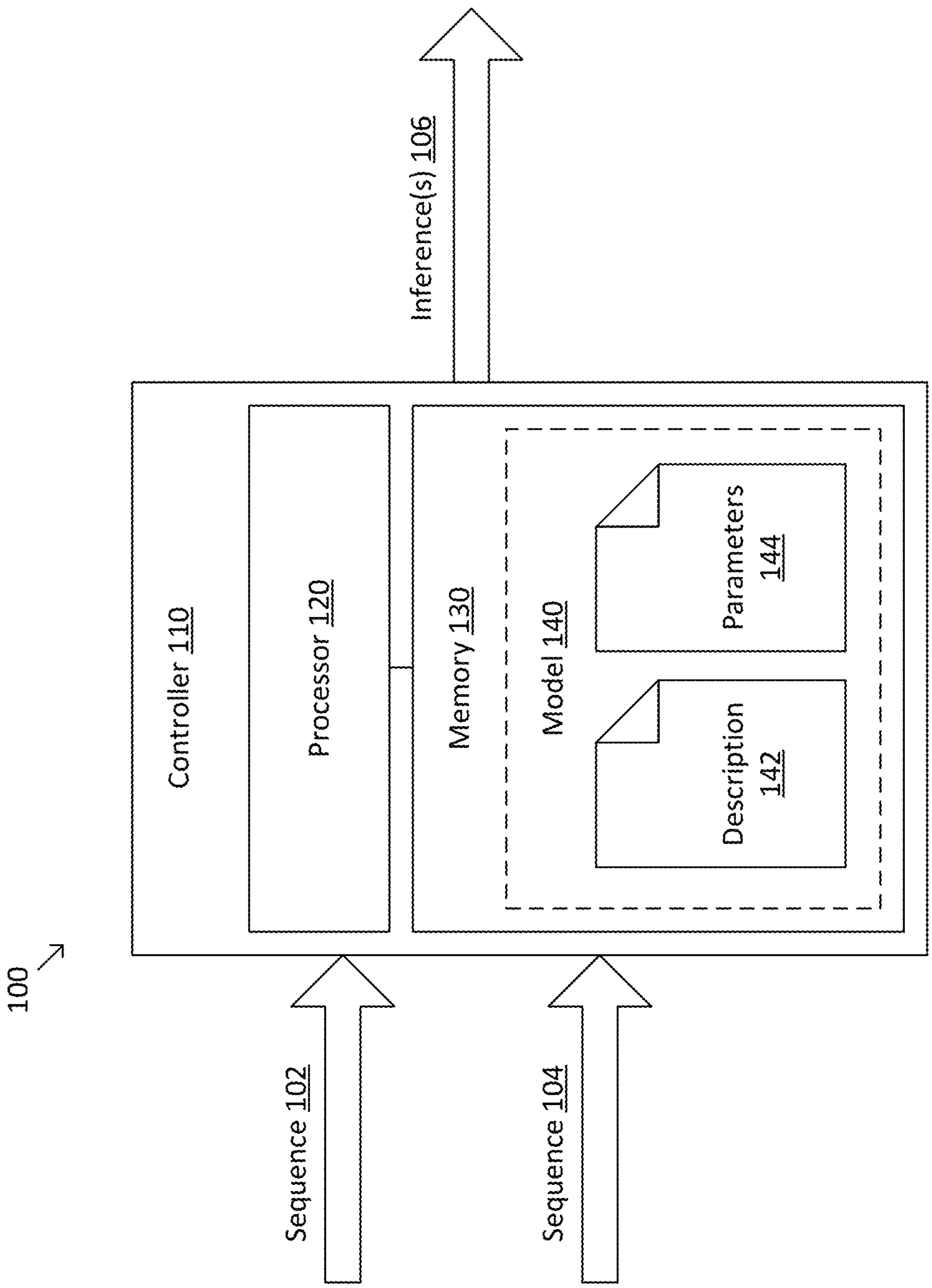
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Inference(s) 106
Controller 110
Processor 120
Memory 130
Model 140
Description 142
Parameters 144
Sequence 102
Sequence 104

FIG. 1

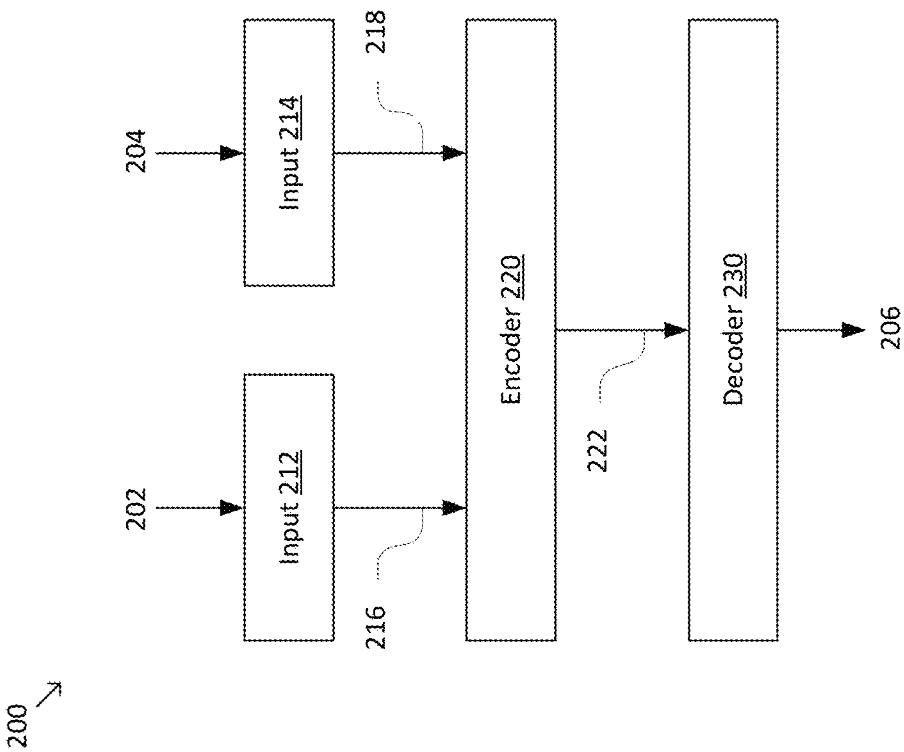

200
202
204
Input 212
Input 214
216
218
Encoder 220
222
Decoder 230
206

FIG. 2

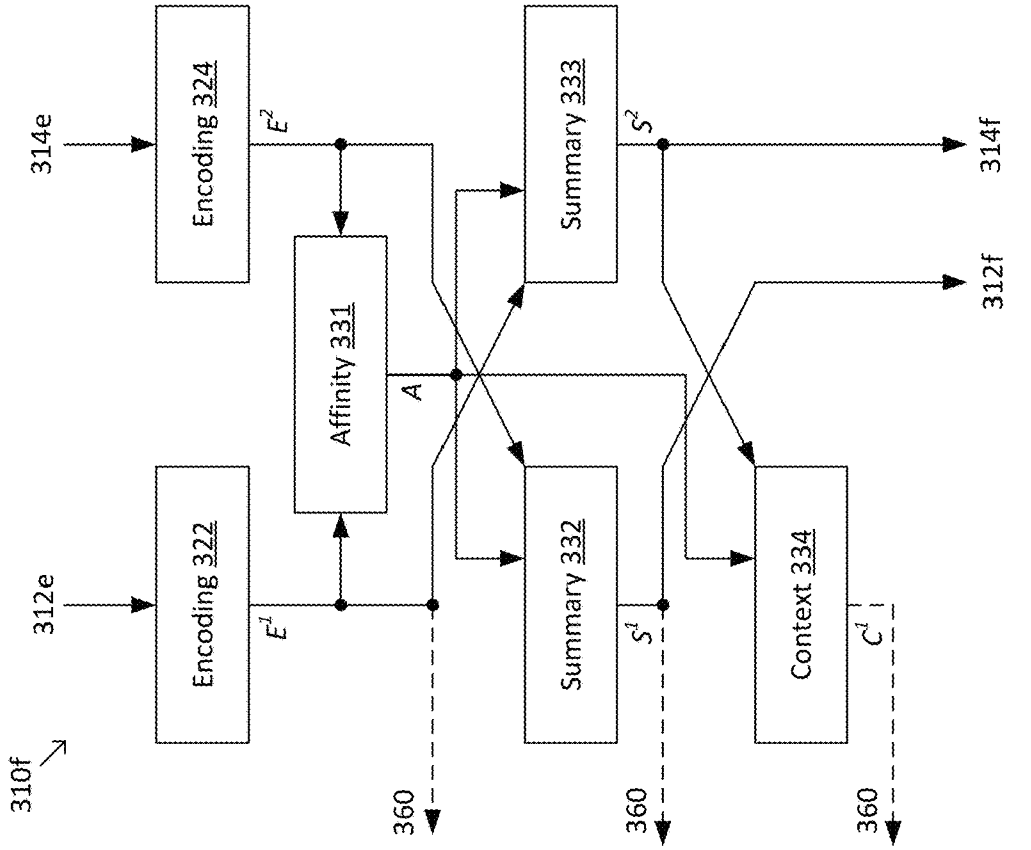

310f
312e
314e
Encoding 322
Encoding 324
Affinity 331
Summary 332
Summary 333
Context 334
E1
E2
A
S1
S2
C1
312f
314f
360
360
360

FIG. 3B

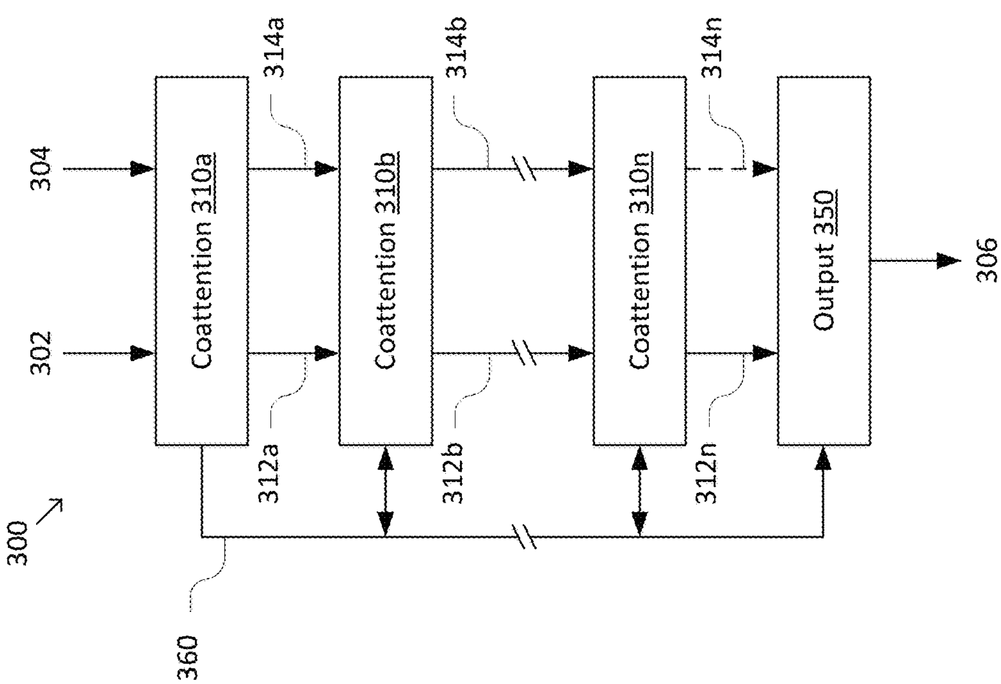

300
302
304
Coattention 310a
Coattention 310b
Coattention 310n
Output 350
312a
312b
312n
314a
314b
314n
306
360

FIG. 3A

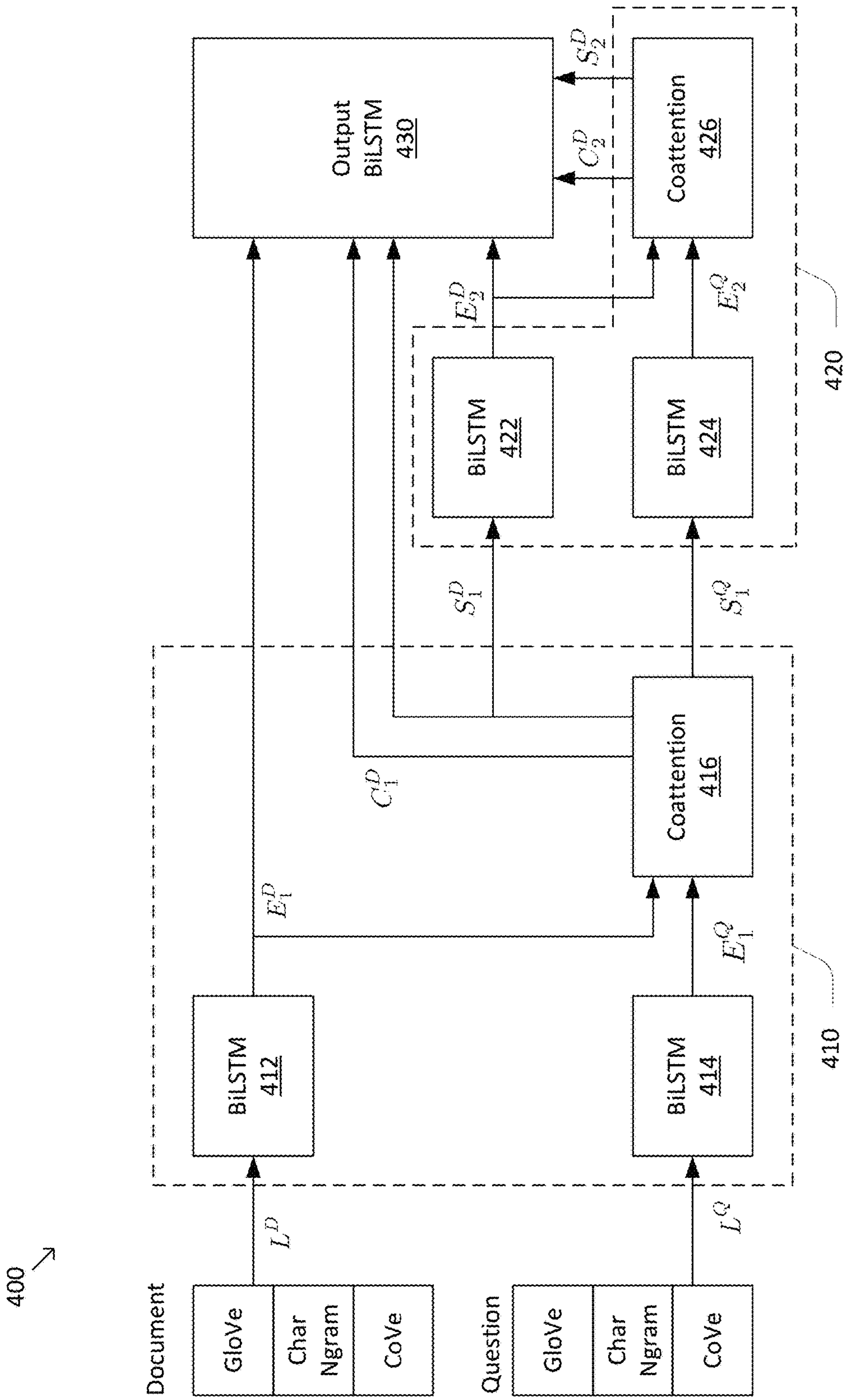

400
Document
GloVe
Char Ngram
CoVe
Question
GloVe
Char Ngram
CoVe
L^D
L^Q
BiLSTM 412
BiLSTM 414
E_1^D
E_1^Q
Coattention 416
C_1^D
410
S_1^D
S_1^Q
BiLSTM 422
BiLSTM 424
E_2^D
E_2^Q
Coattention 426
C_2^D
S_2^D
420
Output BiLSTM 430

FIG. 4

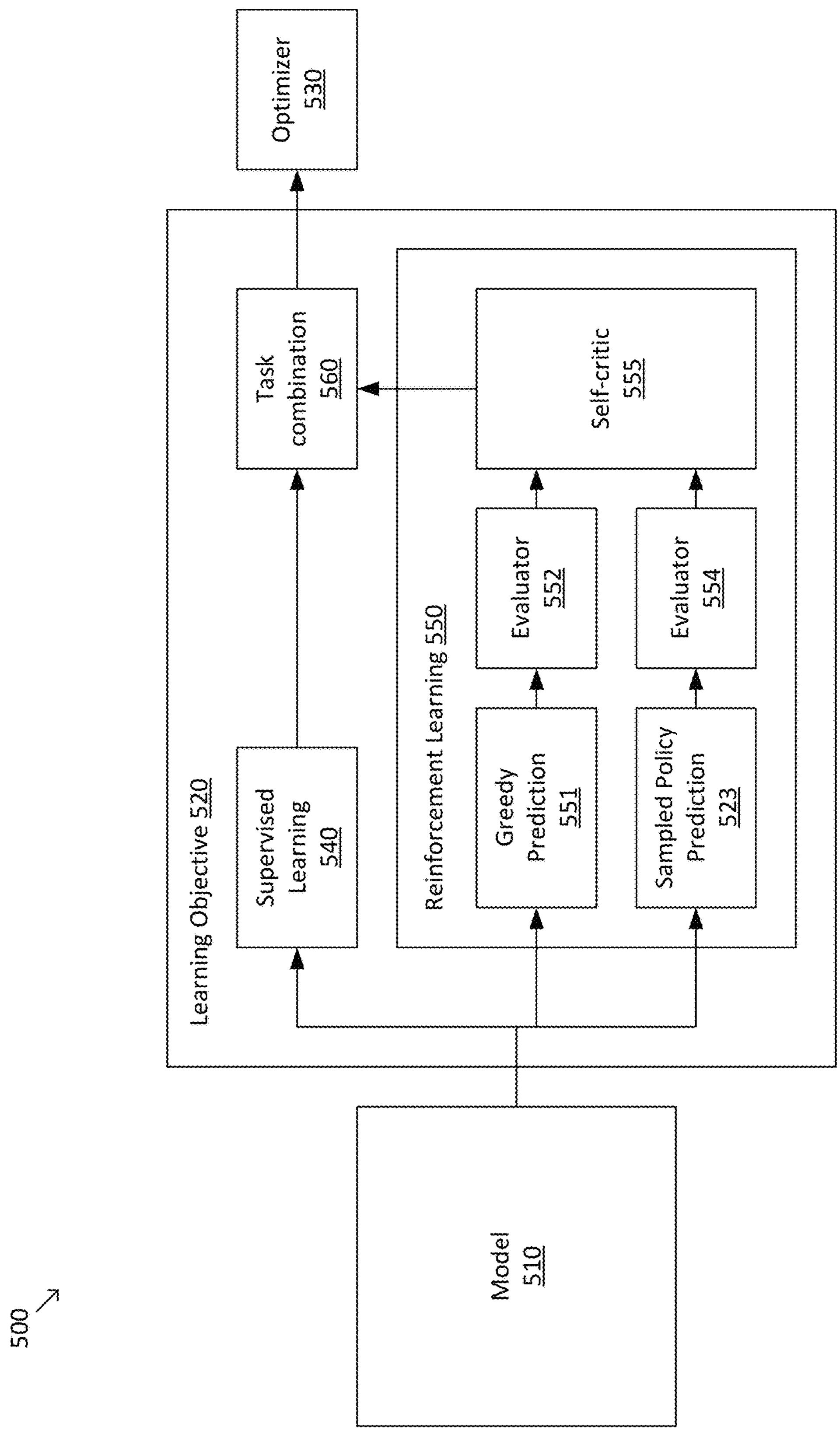

500
Model 510
Learning Objective 520
Supervised Learning 540
Reinforcement Learning 550
Greedy Prediction 551
Sampled Policy Prediction 523
Evaluator 552
Evaluator 554
Self-critic 555
Task combination 560
Optimizer 530

FIG. 5

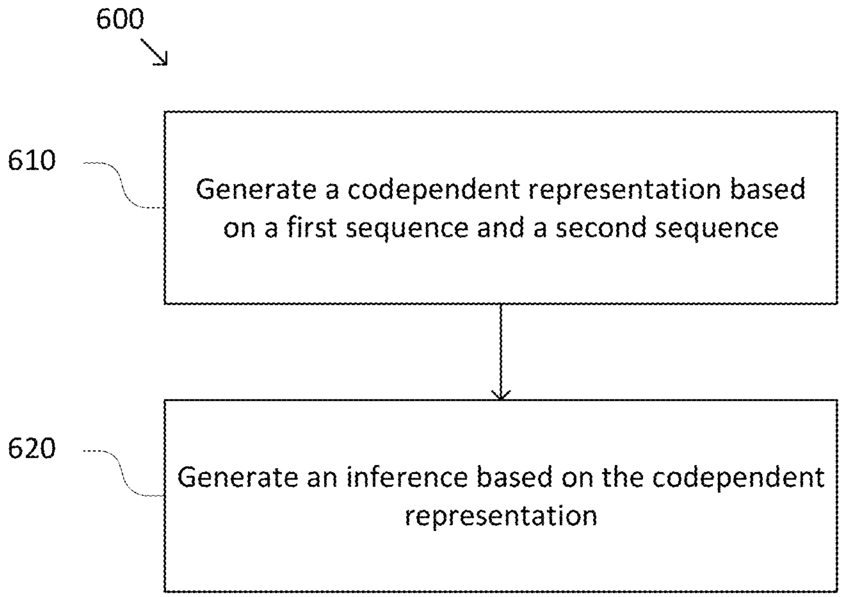

600
610
Generate a codependent representation based on a first sequence and a second sequence
620
Generate an inference based on the codependent representation

FIG. 6

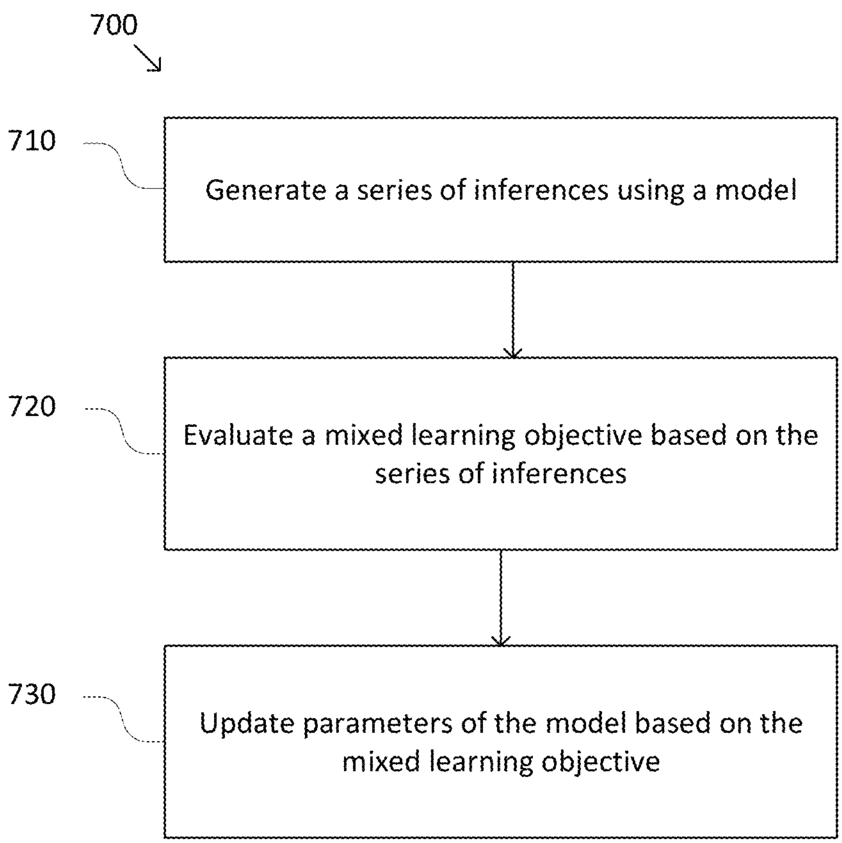

700
710
Generate a series of inferences using a model
720
Evaluate a mixed learning objective based on the series of inferences
730
Update parameters of the model based on the mixed learning objective

FIG. 7

810

Model	Dev EM	Dev F1	Test EM	Test F1	Ens Test EM	Ens Test F1
DCN+	74.5%	83.1%	75.1%	83.1%	78.9%	86.0%
rnet	72.3%	80.6%	72.3%	80.7%	76.9%	84.0%
SEDT	67.9%	77.4%	68.5%	78.0%	73.0%	80.8%
BiDAF	67.7%	77.3%	68.0%	77.3%	73.7%	81.5%
Mnemonic Reader	70.1%	79.6%	69.9%	79.2%	73.7%	81.7%
DCN w/ CoVe	71.3%	79.9%	-	-	-	-
ReasoNet	-	-	69.1%	78.9%	73.4%	81.8%
Document Reader	69.5%	78.8%	70.0%	79.0%	-	-
FastQA	70.3%	78.5%	70.8%	78.9%		
DCN	65.4%	75.6%	66.2%	75.9%	71.6%	80.4%

FIG. 8A

822 824 826

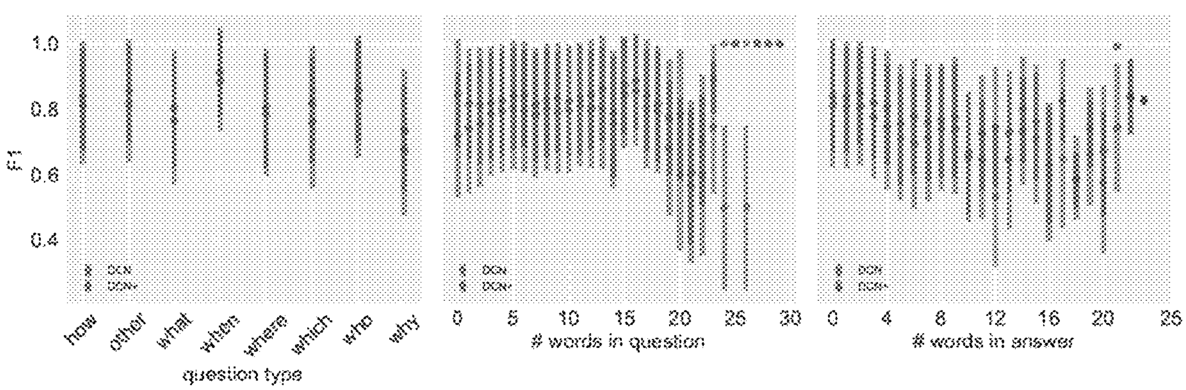


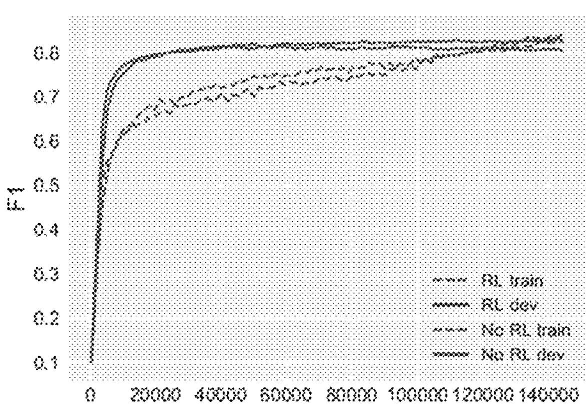
FIG. 8B

830

Model	Dev EM	Δ EM	Dev F1	Δ F1
DCN+	74.5%		83.1%	
- Deep residual coattention	73.1%	1.4%	81.5%	1.6%
- Mixed objective	73.8%	0.7%	82.1%	1.0%

FIG. 8C

842



844

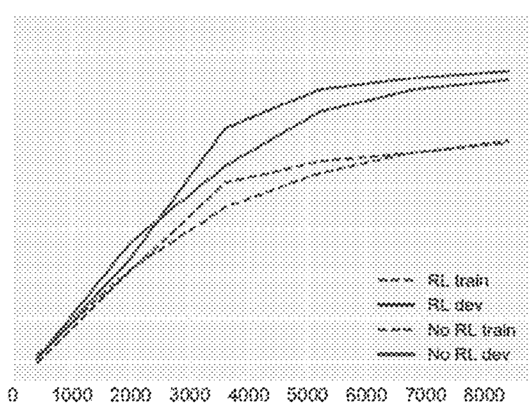


FIG. 8D

GENERATING DUAL SEQUENCE INFERENCES USING A NEURAL NETWORK MODEL

RELATED APPLICATIONS

The present application is a continuation of U.S. application Ser. No. 15/881,582, filed Jan. 26, 2018, now allowed, and also claims priority to U.S. Provisional Patent Application No. 62/578,380, filed Oct. 27, 2017, entitled "DCN+: Mixed Objective and Deep Residual Coattention for Question Answering," which is hereby incorporated by reference in its entirety.

TECHNICAL FIELD

Embodiments of the present disclosure relate generally to neural network models and more particularly to neural network models for dual sequence inference.

BACKGROUND

Neural networks have demonstrated great promise as a technique for automatically analyzing real-world information with human-like accuracy. In general, neural network models receive input information and make predictions based on the input information. For example, a neural network classifier may predict a class of the input information among a predetermined set of classes. Whereas other approaches to analyzing real-world information may involve hard-coded processes, statistical analysis, and/or the like, neural networks learn to make predictions gradually, by a process of trial and error, using a machine learning process. A given neural network model may be trained using a large number of training examples, proceeding iteratively until the neural network model begins to consistently make similar inferences from the training examples that a human might make. Neural network models have been shown to outperform and/or have the potential to outperform other computing techniques in a number of applications. Indeed, some applications have even been identified in which neural networking models exceed human-level performance.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a simplified diagram of a system for dual sequence inference according to some embodiments.

FIG. **2** is a simplified diagram of a model for dual sequence inference according to some embodiments.

FIGS. **3**A and **3**B are simplified diagrams of a deep coattention encoder according to some embodiments.

FIG. **4** is a simplified diagram of a deep coattention encoder of a question answering model according to some embodiments.

FIG. **5** is a simplified diagram of a training configuration with a mixed learning objective according to some embodiments.

FIG. **6** is a simplified diagram of a method for dual sequence inference according to some embodiments.

FIG. **7** is a simplified diagram of a method for training a neural network model using a mixed learning objective according to some embodiments.

FIGS. **8**A-**8**D are simplified diagrams of an experimental evaluation of a question answering model according to some embodiments.

DETAILED DESCRIPTION

Question answering (QA) is one class of problems to which neural networks may be been applied. In QA applications, a QA model receives a sequence of text representing a document and a sequence of text representing a question. The goal of the QA model is to accurately predict a portion of the document (e.g., a span of text in the document) that answers the question. To illustrate, suppose a document provided to a QA model includes the text "Some believe that the Golden State Warriors team of 2017 is one of the greatest teams in NBA history," and further suppose that a question provided to the QA model includes the text "Which team is considered to be one of the greatest teams in NBA history?" The ground truth answer to the question is the span of text in the document that reads "the Golden State Warriors team of 2017." Accordingly, the QA model should identify the span of text in the document that matches the ground truth answer. At the very least, the QA model should identify an overlapping span of text that is close in meaning to the ground truth answer (e.g., "Golden State Warriors").

QA models are applicable to a variety of technologies, including search engines, digital personal assistants, chatbots, and/or the like. Some QA models may be designed for general-purpose applications (e.g., capable of answering a wide variety of question and/or document types, question and/or document lengths, answer lengths, and/or the like). Others may be tailored for specialized applications.

The performance of QA models may be compared or benchmarked by testing different models on a shared dataset, such as, for example, the Stanford Question Answering Dataset (SQuAD). The accuracy of each model may be measured by evaluating one or more metrics, such as exact match accuracy (e.g., the percentage of trials where the predicted answer exactly matches the ground truth answer), F1 score accuracy (which assesses the amount of overlap between the predicted answer and the ground truth answer), and/or the like. State of art QA models achieve less than or equal to 72.3% exact match accuracy and less than or equal to 80.7% F1 score accuracy on SQuAD, or when ensembled, less than or equal to 76.9% exact match accuracy and less than or equal to 84.0% F1 score accuracy.

Accordingly, it is desirable to develop QA models that achieve higher accuracy than current state of art QA models. It is also desirable to develop techniques for training QA models faster and/or with less training data. More generally, it is desirable to developed improved neural network models that generate inferences based on a pair of input sequences, referred to herein as dual sequence inference. Although some dual sequence inference models receive text input sequences, such as the QA models described above, it is to be understood that the dual sequence inference models may operate on a wide variety of types of input sequences, including but not limited to text sequences, audio sequences, image sequences (e.g., video), and/or the like.

FIG. **1** is a simplified diagram of a system **100** for dual sequence inference according to some embodiments. According to some embodiments, system **100** may receive a first sequence **102** and a second sequence **104** and generate an inference **106** (and/or multiple inferences). In QA applications, sequence **102** may correspond to a text sequence representing a document, sequence **104** may correspond to a text sequence representing a question, and inference **106** may correspond to a span of text in the document representing an answer to the question. However, it is to be understood that QA is merely one example, and that system **100** may be used in a wide variety of applications, including non-QA applications such as textual entailment (TE) applications.

As depicted in FIG. **1**, system **100** includes a controller **110**. In some embodiments, controller **110** may include a processor **120** (e.g., one or more hardware processors). Although processor **120** may include one or more general purpose central processing units (CPUs), processor **120** may additionally or alternately include at least one processor that provides accelerated performance when evaluating neural network models. For example, processor **120** may include a graphics processing unit (GPU), an application specific integrated circuit (ASIC), a field programmable gate array (FPGA), a tensor processing unit (TPU), a digital signal processor (DSP), a single-instruction multiple-data (SIMD) processor, and/or the like. Generally, such processors may accelerate various computing tasks associated with evaluating neural network models (e.g., training, prediction, preprocessing, and/or the like) by an order of magnitude or more in comparison to a general purpose CPU.

Controller **110** may further include a memory **130** (e.g., one or more non-transitory memories). Memory **130** may include various types of short-term and/or long-term storage modules including cache memory, static random access memory (SRAM), dynamic random access memory (DRAM), non-volatile memory (NVM), flash memory, solid state drives (SSD), hard disk drives (HDD), optical storage media, magnetic tape, and/or the like. In some embodiments, memory **130** may store instructions that are executable by processor **120** to cause processor **120** to perform operations corresponding to processes disclosed herein and described in more detail below.

Processor **120** and/or memory **130** may be arranged in any suitable physical arrangement. In some embodiments, processor **120** and/or memory **130** may be implemented on a same board, in a same package (e.g., system-in-package), on a same chip (e.g., system-on-chip), and/or the like. In some embodiments, processor **120** and/or memory **130** may include distributed, virtualized, and/or containerized computing resources. Consistent with such embodiments, processor **120** and/or memory **130** may be located in one or more data centers and/or cloud computing facilities.

In some embodiments, memory **130** may store a model **140** that is evaluated by processor **120** during dual sequence inference. Model **140** may include a plurality of neural network layers. Examples of neural network layers include densely connected layers, convolutional layers, recurrent layers, pooling layers, dropout layers, and/or the like. In some embodiments, model **140** may include at least one hidden layer that is not directly connected to either an input or an output of the neural network. Model **140** may further include a plurality of model parameters (e.g., weights and/or biases) that are learned according to a machine learning process. Examples of machine learning processes include supervised learning, reinforcement learning, unsupervised learning, and/or the like. Embodiments of model **140** are described in further detail below with reference to FIGS. **2-7**.

Model **140** may be stored in memory **130** using any number of files and/or data structures. As depicted in FIG. **1**, model **140** includes a model description file **142** that defines a computational graph of model **140** (e.g., a sequence of neural network layers) and a model parameters file **144** that stores parameters of model **140** (e.g., weights and/or biases). In general, model description file **142** and/or model parameters file **144** may be store information associated with model **140** in any suitable format, including but not limited to structured, unstructured, serialized, and/or database formats.

FIG. **2** is a simplified diagram of a model **200** for dual sequence inference according to some embodiments. According to some embodiments consistent with FIG. **1**, model **200** may be used to implement model **140**. In some embodiments, model **200** may receive a first sequence **202** and a second sequence **204** and generate an inference **206** (and/or multiple inferences). In embodiments consistent with FIG. **1**, sequences **202** and **204** and inference **206** may generally correspond to sequences **102** and **104** and inference **106**, respectively.

Model **200** may include a first input stage **212** and a second input stage **214** that receive sequences **202** and **204**, respectively. Input stage **212** generates an input representation **216** of sequence **202**, and input stage **214** generates an input representation **218** of sequence **204**. In some embodiments, input representations **216** and/or **218** may correspond to vector representations of sequences **202** and/or **204**, respectively. For example, when sequences **202** and/or **204** correspond to text sequences, input stages **212** and/or **214** may generate the corresponding vector representations by (1) tokenizing the text sequences and (2) embedding the tokenized text sequences in a vector space. Tokenizing the text sequences may include identifying tokens within the text sequences, where examples of tokens include characters, character n-grams, words, word n-grams, lemmas, phrases (e.g., noun phrases), sentences, paragraphs, and/or the like. Embedding the tokenized text sequences may include mapping each token to a vector representation in a multidimensional vector space. For example, a token corresponding to a word may be mapped to a 300-dimensional vector representation of the word using pre-trained GloVe vectors.

Model **200** may further include an encoder stage **220** that receives input representations **216** and **218** and generates a codependent representation **222** of sequences **202** and/or **204** that depends on each of sequences **202** and **204**. For example, in QA applications, where sequence **202** corresponds to a document and sequence **204** corresponds to a question, codependent representation **222** may depend on both the document and the question. This is in contrast to input stages **212** and **214**, which analyze the document and the question independently of one another. In this regard, encoder stage **220** may harness the context that the question provides when analyzing the document and/or vice versa. In some embodiments, encoder stage **220** may include a deep coattention encoder, embodiments of which are described in greater detail below with reference to FIGS. **3-4**.

Model **200** may further include a decoder stage **230** that receives codependent representation **222** and generates inference **206**. In QA applications, decoder stage **230** may include a dynamic decoder that iteratively predicts a span in sequence **202** that contains the answer to the question corresponding to second sequence **204**. For example, the dynamic decoder may output a pair of pointers corresponding to the start and end of the predicted span. The iterative process may terminate when the prediction converges (e.g., when a change in the prediction between consecutive iterations is below a threshold). Embodiments of dynamic decoders are described in further detail in "Dynamic Coattention Networks for Question Answering," in *ICLR*, 2017, to Xiong et al., which is herein incorporated by reference in its entirety.

According to some embodiments, model **200** may correspond to a computational graph, in which case input stages **212** and/or **214**, encoder stage **220**, and/or decoder stage **230** may correspond to collections of nodes in the computational graph. Consistent with such embodiments, various representations used by model **200**, such as input representations **216** and/or **218**, codependent representation **222**, and/or any intermediate representations used by model **200**, may correspond to real-valued tensors (e.g., scalars, vectors, multi-dimensional arrays, and/or the like) that are passed along edges of the computational graph. Moreover, each node of the computation graph may perform one or more tensor operations, e.g., transforming one or more input representations of the node into one or more output representations of the node. Examples of tensor operations performed at various nodes may include matrix multiplication, n-dimensional convolution, normalization, element-wise operations, and/or the like.

FIGS. **3**A and **3**B are simplified diagrams of a deep coattention encoder **300** according to some embodiments. According to some embodiments consistent with FIGS. **1-2**, deep coattention encoder **300** may be used to implement encoder stage **220**. Consistent with such embodiments, deep coattention encoder **300** may receive an input representation **302** of a first sequence and an input representation **304** of a second sequence and may generate a codependent representation **306** that depends on each of the first and second sequences. In some embodiments, input representations **302** and/or **304** may be generated by respective input stages, such as input stages **212** and/or **214**.

Deep coattention encoder **300** may include a plurality of coattention layers **310***a-n* arranged sequentially (e.g., in a pipelined fashion). Each of coattention layer **310***a-n* generates a respective first summary representation **312***a-n* corresponding to the first sequence and a respective second summary representation **314***a-n* corresponding to the second sequence based on a pair of layer input representations. In the case of the first layer in the sequence (i.e., coattention layer **310***a*), the pair of layer input representations corresponds to input representations **302** and **304**. In the case of other layers in the sequence (i.e., coattention layers **310***b-n*), the pair of layer input representations corresponds to summary representations **312***a-n* and **314***a-n* generated by a preceding layer in the sequence. In the case of the last layer in the sequence (i.e., coattention layer **310***n*), either of summary representations **312***n* and/or **314***n* may be omitted and/or optional. For example, as depicted in FIG. **3**A, summary representation **314***n* is optional.

In comparison to encoders that include a single coattention layer, deep coattention encoder **300** may be capable of generating a richer codependent representation **306** that contains more relevant information associated with the first and second input sequences. For example, deep coattention encoder **300** may include more trainable model parameters than single-layer coattention encoders. Moreover, whereas a single-layer coattention encoder may allow each sequence to attend to the other sequence, deep coattention encoder **300** may allow each sequence to attend to itself as well as to the other sequence. Consequently, deep coattention encoder **300** may be capable of achieving higher accuracy than single-layer coattention encoders in dual sequence inference problems, such as QA problems.

FIG. **3**B depicts a coattention layer **310***f*, which may be used to implement one or more of coattention layers **310***a-n* depicted in FIG. **3**A. As depicted in FIG. **3**B, coattention layer **310***f* includes a pair of encoding sub-layers **322** and **324** that each receive a respective layer input representation **312***e* and **314***e* and generate a respective encoded representation E^1 and E^2. In some embodiments, encoding sub-layers **322** and/or **324** may include one or more recurrent neural network (RNN) layers. In general, an RNN layer injects sequence-related information (e.g., temporal information) into the transformed representation. For example, the RNN layer may include a sequence of simple RNN cells, long short-term memory (LSTM) cells, gated recurrent units (GRUs), and/or the like. In some examples, the RNN layer may be bi-directional, e.g., a bi-directional LSTM (Bi-LSTM) layer. Additionally or alternately, encoding sub-layers **322** and/or **324** may include a feed-forward neural network layer, and/or may perform any other suitable transformation or set of transformation on layer input representations **312***e* and **314***e*. In some embodiments, encoding sub-layers **322** and/or **324** may include one or more non-linear activation functions (e.g., rectified linear units (ReLU), sigmoid, hypertangent (tanh), softmax, and/or the like).

In illustrative embodiments, encoded representations E^1 and E^2 may correspond to real-valued tensors determined according to the following equations:

$$E^1=\text{encoding}^1(L^1)\in\mathbb{R}^{h\times m} \quad (1)$$

$$E^2=\text{encoding}^2(L^2)\in\mathbb{R}^{h\times n} \quad (2)$$

where L^1 and L^2 denote the respective layer input representations; m and n denote the length of the first and second sequences, respectively; h denotes the number of dimensions of the encoded representations; and $\text{encoding}^1(X)$ and $\text{encoding}^2(X)$ denote respective encoding operations (e.g., RNN operations, bi-LSTM operations, feed-forward operations, and/or the like) applied to an input X.

Coattention layer **310***f* may further include an affinity node **331** that determines a set of affinity scores corresponding to each pair of items in in encoded representations E^1 and E^2. In general, an affinity score may be large for a related pair of items and small for an unrelated pair of items. For example, when the words “dog,” and “tree” appear in the first sequence and the word “puppy” appears in the second sequence, the pairing (“dog”, “puppy”) is likely to receive a high affinity scores because the words refer to the same type of animal, whereas the pairing (“tree”, “puppy”) is likely to receive a low affinity score because they are unrelated concepts. In illustrative embodiments, the set of affinity scores may be determined according to the following equation:

$$A=(E^1)^T E^2\in\mathbb{R}^{m\times n} \quad (3)$$

where A denotes an affinity matrix containing the set of affinity scores and X^T denotes the transpose of the matrix X.

Coattention layer **310***f* may further include a pair of summary nodes **332** and **333** that generate summary representations S^1 and S^2, respectively, based on the affinity scores and the encoded representations E^1 and E^2. In illustrative embodiments, summary representations S^1 and S^2 may correspond to real-valued tensors determined according to the following equations:

$$S^1=E^2\text{activation}^1(A^T)\in\mathbb{R}^{h\times m} \quad (4)$$

$$S^2=E^1\text{activation}^2(A)\in\mathbb{R}^{h\times n} \quad (5)$$

where $\text{activation}^1(X)$ and $\text{activation}^2(X)$ denote respective activation operations over the matrix X (e.g., linear, softmax, sigmoid, tanh, ReLU, ELU, and/or the like).

Coattention layer **310***f* may further include a context nodes **334** that generates context representation **312***f* (C^1) based on the affinity scores and summary representations S^2. In illustrative embodiments, context representation C^1 may correspond to a real-valued tensor determined according to the following equation:

$$C^1=S^2\text{activation}^3(A^T)\in\mathbb{R}^{h\times m} \quad (6)$$

The activation operations used by context node **334** may or may not be the same as the activation operations used by summary nodes **332** and/or **333**.

Returning to FIG. **3**A, deep coattention encoder **300** may additionally include an output layer **350** that receives summary representations **312***n* and/or **314***n* from the last layer among the plurality of coattention layers **310***a-n* and generates codependent representation **306**. In some embodiments, output layer **350** may include a neural network layer, such as and RNN, feed-forward neural network, and/or the like.

In some embodiments, deep coattention encoder **300** may include a plurality of model parameters learned according to a machine learning process, such as a supervised learning process, a reinforcement learning process, an unsupervised learning process, and/or the like. However, there are various challenges associated with training the model parameters of deep neural network models, such as a model that includes deep coattention encoder **300**. For example, one approach to training deep neural network models is to iteratively update the model parameters over a set of training data based on the gradient of a learning objective. However, deep neural networks may train slowly, or not at all, due to the degradation of the gradients (e.g., vanishing and/or exploding gradients) at layers far from the output of the neural network model. Accordingly, one challenge associated with deep coattention encoder **300** is to train model parameters associated with layers and/or sub-layers distant from output layer **350** (e.g., coattention layers **310***a* and/or **310***b*).

To address this challenge, deep coattention encoder **300** may include one or more residual connections **360**. Residual connections **360** bypass one or more layers (and/or sub-layers and/or nodes) of deep coattention encoder **300**, thereby reducing the effective distance between deep layers of the network (e.g., coattention layers **310***a* and/or **310***b*) and output layer **350**. In general, residual connections **360** may bypass any number of layers, sub-layers, and/or nodes. As depicted in FIG. **3**B, the source end of residual connections **360** may correspond to any or each of encoded representations E^1 and/or E^2, summary representations S^1 and/or S^2, and/or context representation C^1.

In some embodiments, residual connections **360** may be combined with other inputs at a destination layer. For example, residual connections **360** may be concatenated at the destination. Consistent with such embodiments, the size of the inputs to the destination layer may be increased by the use of residual connections **360**. To the extent that the increase in input size may be undesirable, various techniques may be applied to reduce the size concatenated input. For example, a pooling layer (e.g., max pooling, average pooling, and/or the like), a feed-forward neural network, and/or the like may be used to the reduce the size of the concatenated input. Additionally or alternately, residual connections **360** and/or other inputs may be combined by techniques other than concatenation, such as summation.

FIG. **4** is a simplified diagram of a deep coattention encoder **400** of a QA model according to some embodiments. In some embodiments consistent with FIGS. **1**-**3**B, deep coattention encoder **400** may be used to implement deep coattention encoder **300**. Deep coattention encoder **400** receives first sequence corresponding to a document of m words and a second sequence corresponding to a question of n words. The document and question are processed by respective input encoders, which generally correspond to input stages **212** and/or **214**. As depicted in FIG. **4**, the input encoders generate input representation of the document L^D and an input representation of a question L^Q according to the following equations:

$$L^D=\text{concat}(\text{emb}_{GloVe}(w^D),\text{emb}_{char}(w^D),\text{emb}_{CoVe}(w^D))\in\mathbb{R}^{m\times e} \tag{7}$$

$$L^Q=\text{concat}(\text{emb}_{GloVe}(w^Q),\text{emb}_{char}(w^Q),\text{emb}_{CoVe}(w^Q))\in\mathbb{R}^{n\times e} \tag{8}$$

where $w^D=[w_1^D, w_2^D \ldots w_m^D]$ denotes the set of words in the document, $w^Q=[w_1^Q, w_2^Q \ldots w_n^Q]$ denotes the set of words in the question, $\text{emb}_{GloVe}(w)$ denotes the GloVe embeddings of a set of words, $\text{emb}_{char}(w)$ denotes the character embeddings of a set of words, $\text{emb}_{CoVe}(w)$ denotes a context vector embedding of a set of words, concat(A,B,C) denotes a concatenation between matrices A, B, and C along a feature dimension, m denotes the number of words in the document, n denotes the number of words in the question, and e denotes the total number of dimensions of the word embeddings, character embeddings, and context vector embeddings. In some embodiments, the context vector embeddings are generated by a context vector encoder, such as a two-layer BiLSTM encoder, pretrained on a text corpus, such as the WMT machine translation corpus.

Deep coattention encoder **400** includes a first coattention layer **410**, which generally corresponds to coattention layer **310***a* of deep coattention encoder **300**. The input representations of the document L^D and the question L^Q are received by respective bi-LSTM encoders **412** and **414** of first coattention layer **410**. In some embodiments consistent with FIG. **3**B, bi-LSTM encoders **412** and **414** may correspond to encoding sub-layers **322** and **324**, respectively. Bi-LSTM encoders **412** and **414** generate encoded representations E_1^D and E_1^Q of the document and the question, respectively, according to the following equations:

$$E_1^D=\text{bi-LSTM}_1(L^D)\in\mathbb{R}^{h\times(m+1)} \tag{9}$$

$$E_1^Q=\tanh(W\,\text{bi-LSTM}_1(L^Q)+b)\in\mathbb{R}^{h\times(n+1)} \tag{10}$$

where h denotes the number of dimensions of the encoded representation, W and b denote weights and biases, respectively, of a feed-forward neural network layer, and tanh(x) denotes the hypertangent activation function. A sentinel word is added to the input representation to prevent deep coattention encoder **400** from focusing on a particular part of the input representation, so the number of words in the encoded representation of the document and question is (m+1) and (n+1), respectively.

The encoded representations E_1^D and E_1^Q of the document and the question are received by a coattention sub-layer **416**, which generally corresponds to nodes **331**-**335** as depicted in FIG. **3**B. Based on encoded representations E_1^D and E_1^Q, coattention sub-layer **416** determines an affinity matrix A between the document and the question according to the following equation:

$$A=(E_1^D)^T E_1^Q\in\mathbb{R}^{(m+1)\times(n+1)} \tag{11}$$

As discussed previously, the affinity matrix A contains an affinity score for each pair of words in E_1^D and E_1^Q.

Based on affinity matrix A, coattention sub-layer **416** determines document an question summary representations S_1^D and S_1^Q, respectively, according to the following equations:

$$S_1^D=E_1^Q\text{softmax}(A^T)\in\mathbb{R}^{h\times(m+1)} \tag{12}$$

$$S_1^Q=E_1^D\text{softmax}(A)\in\mathbb{R}^{h\times(n+1)} \tag{13}$$

where softmax(X) denotes the softmax operation over the matrix X that normalizes X column-wise.

Based on affinity matrix A and summary representations S_1^D and S_1^Q, coattention sub-layer **416** determines document context representation C_1^D according to the following equation:

$$C_1^D = S_1^Q \text{softmax}(A^T) \in \mathbb{R}^{h \times m} \quad (14)$$

The sentinel word is removed, such that the number of words in the document context representations C_1^D is m rather than m+1. In some embodiments consistent with FIGS. **3A-3B**, C_1^D may correspond to context representation **312***a*.

Deep coattention encoder **400** further includes a second coattention layer **420** that generally corresponds to coattention layers **310***b* and/or **310***n* of deep coattention encoder **300**. As depicted in FIG. **4**, second coattention layer **420** includes bi-LSTM encoders **422** and **424** and a coattention sub-layer **426**, which generally operate in a similar manner to bi-LSTM encoders **412** and **414** and coattention sub-layer **416** of first coattention layer **410**, as described above. In particular, bi-LSTM encoders **422** and **424** generate encoded representations E_2^D and E_2^Q of the document and the question, respectively. In some embodiments, the size of representations E_2^D and/or E_2^Q may be the same as and/or different from the size of representations E_1^D and/or E_1^Q. In illustrative embodiments, the size of representations E_2^D and/or E_2^Q may be double the size of representations E_1^D and/or E_1^Q (e.g., $E_2^D \in \mathbb{R}^{2h \times m}$ and/or $E_2^Q \in \mathbb{R}^{2h \times n}$. Based on encoded representations E_2^D and E_2^Q, coattention sub-layer **426** generates and outputs one or more of a summary representation of the document S_2^D and/or a coattention context of the document C_2^D.

An output encoder **430** receives the output representations from the preceding layers and generates a codependent representation U of the document according to the following equation:

$$U = \text{bi-LSTM}(\text{concat}(E_1^D; E_2^D; S_1^D; S_2^D; C_1^D; C_2^D)) \in \mathbb{R}^{2h \times n} \quad (17)$$

As indicated above, output encoder **430** receives various representations of the document (e.g., E_1^D, E_2^D, S_1^D, and C_1^D) from bi-LSTM encoder **412**, coattention sub-layer **416**, and BiLSTM encoder **422**, in addition to representations of the document from coattention sub-layer **426** (e.g., S_2^D, and C_2^D. The representations received from earlier layers of deep coattention encoder **400** correspond to residual connections, such as residual connection **360**, that bypass one or more layers and/or sub-layers of the network. In general, the use of residual connections may facilitate training of deep coattention encoder **400** by addressing gradient degradation issues.

FIG. **5** is a simplified diagram of a training configuration **500** with a mixed learning objective according to some embodiments. As depicted in FIG. **5**, training configuration **500** is used to train a model **510**. In some embodiments consistent with FIGS. **1-4**, model **510** may be used to implement model **200**. In some embodiments, training configuration **500** may be used to reduce the amount of time and/or training data used to train model **510**. In some embodiments, model **510** may include a deep coattention encoder, such as deep coattention encoders **300** and/or **400**. However, it is to be understood that training configuration **500** may be used for training a wide variety of model types, including non-QA models and/or models without deep coattention encoders.

According to some embodiments, training configuration **500** may be used to train a plurality of model parameters of model **510**. During training, a large number of training examples (e.g., pairs of input sequences for dual sequence inference applications) are provided to model **510**. The inferences generated by model **510** are compared to a ground truth answers for each of the examples using a learning objective **520**, which determines a loss and/or reward associated with a given inference based on the ground truth answer.

The output of learning objective **520** (e.g., the loss and/or reward) is provided to an optimizer **530** to update the model parameters of model **510**. For example, optimizer **530** may determine the gradient of the objective with respect to the model parameters and adjust the model parameters using backpropagation. In some embodiments, optimizer **530** may include a gradient descent optimizer (e.g., stochastic gradient descent (SGD) optimizer), an ADAM optimizer, an Adagrad optimizer, an RMSprop optimizer, and/or the like. Various parameters may be supplied to optimizer **530** (e.g., a learning rate, a decay parameter, and/or the like) depending on the type of optimizer used.

In some embodiments, model **510** may iteratively generate a series of inferences for a given pair of input sequences. For example, model **510** may include a coattention encoder, such as deep coattention encoder **300**, that generates a codependent representation of the pair of input sequences and a dynamic decoder that iteratively generates inferences based on the codependent representation until the inferences converge (e.g., when the inferences change by less than a threshold amount during consecutive iterations).

In some embodiments, learning objective **520** may determine the loss and/or reward associated with a given series of inferences generated by model **510** using a supervised learning objective **540**. In some embodiments, supervised learning objective **540** may determine loss and/or reward by evaluating a differentiable objective function, such as the cross-entropy loss function. In QA applications, where each inference corresponds to a span in a document defined by a start position and an end position, the cross-entropy loss may be defined as follows:

$$\text{loss}_{ce}(\Theta) = -\Sigma_t[\log p_t^{start}(s|s_{t-1}, e_{t-1}; \Theta) + \log p_t^{end}(e|s_{t-1}, e_{t-1}; \Theta)] \quad (18)$$

where $\text{loss}_{ce}(\Theta)$ is the cross-entropy loss for a given set of model parameters Θ; $p_t^{start} \in \mathbb{R}^m$ and $p_t^{end} \in \mathbb{R}^m$ are the distributions of the start and end positions, respectively, estimated by the dynamic decoder at decoder time step t; s and e are the ground truth start and end positions, respectively; and s_{t-1} and e_{t-1} are the estimates of the start and end positions at the previous decoder time step. Because the cross-entropy loss function is differentiable with respect to the model parameters, it is generally straightforward for optimizer **530** to determine the gradient and update the parameters at each training step by back propagation.

Although supervised learning objective **540** may provide a useful starting point for assessing the accuracy of the inferences generated by model **510**, this approach may on occasion produce undesirable results. For example, supervised learning objective **540** may punish and/or reward certain inferences in a non-intuitive or unwarranted manner. In QA applications, supervised learning objective **540** may correspond to the "exact match" accuracy metric discussed previously. In this regard, supervised learning objective **540** may determine loss and/or rewards in a binary manner, in which inferences are regarded as being correct when they exactly correspond to the ground truth answer and incorrect otherwise. However, the exact match metric does not provide a notion of being "close" to the correct answer; each inference is regarded as either right or wrong, with no in-between.

Other evaluation metrics, such as the F1 score, are non-binary. In general, non-binary evaluation metrics account for the fact that some inferences may be regarded as being at least partially correct, even if they do not exactly match the ground truth answer. For example, the F1 score partially rewards inferences that overlap with, but do not exactly match, the ground truth answer. In this regard, non-binary evaluation metrics, such as the F1 score, may provide a more nuanced comparison between the inferences and the ground truth than binary evaluation metrics, such as the exact match metric.

Accordingly, learning objective **520** may include a reinforcement learning objective **550** based on a non-binary evaluation metric, such as the F1 score. In some embodiments, reinforcement learning objective **550** may use the non-binary evaluation metric to define a loss and/or reward function for a reinforcement learning process. For example, reinforcement learning objective **550** may evaluate to the negative of the expected reward over trajectories τ given a set of model parameters, where each of the trajectories r corresponds to a sequence of start and end positions at each decoder time step. In illustrative embodiments, reinforcement learning objective **550** may be evaluated as follows:

$$\text{baseline} = F_1(ans(s_T,\ e_T),\ ans(s,\ e)) \tag{19}$$

$$R = F_1(ans(\hat{s}_T,\ \hat{e}_T),\ ans(s,\ e)) - \text{baseline} \tag{20}$$

$$\text{loss}_{rl}(\Theta) = -\mathbb{E}_{\hat{\tau}\sim p_\tau}[R] \tag{21}$$

where F_1 denotes the F1 word overlap scoring function; baseline denotes the baseline F1 score; ans(x, y) denotes the answer span retrieved from the document based on a given start position x and end position y; s and e are the ground truth start and end positions, respectively; s_T and e_T are the baseline start and end positions, respectively, at the last decoder time step T; R is the reinforcement learning reward function; $\hat{s}_T$ and $\hat{e}_T$ are the start an end positions, respectively, of the sampled trajectory $\hat{\tau}$ at the last decoder time step T; $\text{loss}_{rl}(\Theta)$ is the reinforcement learning loss for a given set of model parameters Θ; and p_τ is the probability distribution of trajectories τ.

In some embodiments, reinforcement learning objective **550** may include a greedy prediction module **551** that determines s_T and e_T (the start and end positions of the baseline, as defined in Equation 19) in a greedy fashion without a teacher forcing on the start position. Reinforcement learning objective **550** may further include a first evaluator **552** that evaluates Equation 19 to determine the baseline F1 score based on s_T and e_T. In some embodiments, reinforcement learning objective **550** may include a sampled policy prediction module **523** that determines $\hat{s}_T$ and $\hat{e}_T$ and a second evaluator **554** that determines the policy F1 score based on $\hat{s}_T$ and $\hat{e}_T$. The policy F1 score corresponds to the first term, $F_1(ans(\hat{s}_T, \hat{e}_T), ans(s, e))$, of Equation 20. Reinforcement learning objective **550** further includes a self-critic module **555** that subtracts the baseline F1 score from the policy F1 score to obtain the reinforcement learning loss defined by Equation 21.

In some embodiments, learning objective **520** may include a task combination module **560** to combine supervised learning objective **540** and reinforcement learning objective **550**. In some embodiments, combining supervised learning objective **540** and reinforcement learning objective **550** (as opposed to using one or the other) may accelerate the training of model **510**. More specifically, the use of supervised learning objective **540** may accelerate policy learning according to reinforcement learning objective **550** by pruning the space of candidate trajectories. For example, in QA applications, the use of reinforcement learning objective **550** (without supervised learning objective **540**) may result in slow training due to the large space of potential answers, documents, and/or questions.

In illustrative embodiments, learning objective **520** may include a task combination module **560** that combines supervised learning objective **540** and reinforcement learning objective **550** using homoscedastic uncertainty as task-dependent weightings according to the following equation:

$$\text{loss} = \frac{1}{2\sigma_{ce}^2}\text{loss}_{ce}(\Theta) + \frac{1}{2\sigma_{rl}^2}\text{loss}_{rl}(\Theta) + \log(\sigma_{ce}^2) + \log(\sigma_{rl}^2) \tag{22}$$

where σ_{ce} and σ_{rl} are learnable parameters.

Unlike the cross-entropy loss function, the reinforcement learning loss function used by reinforcement learning objective **550** may not be differentiable. Accordingly, optimizer **530** may use estimation techniques to determine the gradient of associated with reinforcement learning objective **550**. According to some embodiments, the gradient associated with reinforcement learning objective **550** may be approximated using a single Monte-Carlo sample τ drawn from the probability distribution p_τ according to the following equation:

$$\nabla_\Theta \text{loss}_{rl}(\Theta) \approx -R\nabla_\Theta\left(\Sigma_t^T\left(\log p_t^{start}(\hat{s}_t;\Theta) + \log p_t^{end}(\hat{e}_T,\ \Theta)\right)\right) \tag{23}$$

where all terms are as previously defined. Based on the approximated gradient of reinforcement learning objective **550** with respect to the model parameters Θ, optimizer **530** may proceed to update the parameters of model **510** based on the combination of supervised learning objective **540** and reinforcement learning objective **550**.

FIG. **6** is a simplified diagram of a method **600** for dual sequence inference according to some embodiments. According to some embodiments consistent with FIGS. **1**-**5**, method **600** may be performed using a processor, such as processor **120**. In some embodiments, method **600** may be performed by evaluating a neural network model, such as model **140** and/or **200**. In some embodiments, the neural network model may include a plurality of model parameters learned according to a machine learning process.

At a process **610**, a codependent representation is generated based on a first sequence and a second sequence. In some embodiments, the codependent representation may be generated by an encoder stage of the neural network model. In illustrative embodiments, the encoder stage may be implemented using a deep coattention encoder, such as deep coattention encoder **300** and/or **400**. In some embodiments the first and second sequence may correspond to text sequences, audio sequences, image sequences (e.g., video), and/or the like. In QA applications, the first sequence may correspond to a document and the second sequence may correspond to a question.

At a process **620**, an inference is generated based on the codependent representation. In some embodiments, the inference may be generated using a decoder stage of the model, such as decoder stage **230**. In some embodiments, the decoder model may include a dynamic decoder model that iteratively generates a series of inferences based on the codependent representation. In QA applications, the inference may identify a span of text in the document that answers the question.

FIG. **7** is a simplified diagram of a method **700** for training a neural network model using a mixed learning objective according to some embodiments. According to some embodiments consistent with FIGS. **1-6**, method **700** may be used to train a neural network model, such as model **140** and/or **200**. During training, the model may be configured in a training configuration, such as training configuration **500**. In some examples, method **700** may be performed iteratively over a large number of training examples to gradually train the neural network model.

At a process **710**, a series of inferences is generated using the neural network model. In some embodiments, the series of inferences may be generated based on a training example that includes a first training sequence and a second training sequence. In some embodiments, the series of inferences may be generated according to method **600**, in which an encoder stage of the neural network model generates a codependent representation based on the first and second training sequences. Consistent with such embodiments, the series of inferences may correspond to a series of inferences generated by a dynamic decoder based on the codependent representation.

At a process **720**, a mixed learning objective is evaluated based on the series of inferences. In some embodiments, the mixed learning objective may correspond to learning objective **520**. Consistent with such embodiments, the mixed learning objective may include a supervised learning objective, such as supervised learning objective **540**, and a reinforcement learning objective, such as reinforcement learning objective **550**. Whereas the supervised learning objective may determine a loss and/or reward independently at each decoder step (e.g., independently at each of the series of inferences), the reinforcement learning objective may determine an expected loss and/or reward over an entire trajectory (e.g., collectively over the series of inferences). In some examples, the reinforcement learning objective may determine the expected loss and/or reward using a non-binary evaluation metric, such as the F1 evaluation metric.

At a process **730**, the parameters of the neural network model are updated based on the mixed learning objective. In some embodiments, the model parameters may be updated using an optimizer, such as optimizer **530**. In some embodiments, the parameters may be updated by determining a gradient of the mixed learning objective with respect to the model parameters and updating the parameters based on the gradient. The gradient of differentiable components of the mixed learning objective, such as the supervised learning objective component, may be determined by back propagation. To the extent that the component of the mixed learning objective associated with the reinforcement learning objective may not be differentiable, the gradient may be estimated, e.g., using Monte Carlo techniques.

FIGS. **8**A-**8**D are simplified diagrams of an experimental evaluation of a QA model according to some embodiments. The QA model being evaluated includes a deep coattention encoder, configured as depicted in FIG. **4**, and is trained on the Stanford Question Answering Dataset (SQuAD) using a mixed learning objective, with a training configuration as depicted in FIG. **5**.

FIG. **8**A depicts a table **810** that compares the accuracy of a QA model that includes the deep coattention encoder (top row) to the accuracy of QA models that do not include the deep coattention encoder (other rows). The training and testing is performed on SQuAD. As indicated in the table, the QA model that includes the deep coattention encoder achieves the highest accuracy across all metrics, including 75.1% exact match accuracy (Test EM), 83.1% F1 score accuracy (Test F1), 78.9% ensemble exact match accuracy (Ens Test F1), and 86.0% ensemble F1 accuracy (Ens Test F1).

FIG. **8**B depicts a series of plots **822**, **824**, and **826** that compare the accuracy of a QA model that includes a deep coattention encoder to a model that includes a single-layer coattention encoder. In particular, plot **822** plots F1 score accuracy as a function of question type (e.g., "who," "what," "where," "when," "why," "how," "which," and "other"). As indicated, the QA model that includes the deep coattention encoder outperforms the model that includes the single-layer coattention encoder for every question type. Plot **824** plots F1 score accuracy as a function of the number of words in the question. As indicated, the QA model that includes the deep coattention encoder outperforms the QA model that includes the single-layer coattention encoder for almost every length of question. Plot **826** plots F1 score accuracy as a function of the number of words in the answer. As indicated, the QA model that includes the deep coattention encoder outperforms the QA model that includes the single-layer coattention encoder for almost every length of answer.

FIG. **8**C depicts a table **830** with results of an ablation study performed on the QA model. The ablation study isolates the contribution of various features (e.g., a deep coattention encoder, as depicted in FIG. **4**, and/or a training configuration with a mixed learning objective, as depicted in FIG. **5**) to the overall improvement in accuracy of the QA model. The top row corresponds to a QA model with a deep coattention encoder trained with a mixed learning objective. The second row corresponds to a QA model with a single-layer coattention encoder trained with a mixed learning objective. As indicated, the deep coattention layer is responsible for a 1.4% improvement in exact match accuracy and a 1.6% improvement in F1 score accuracy. Meanwhile, the mixed learning objective is responsible for an 0.7% improvement in exact match accuracy and a 1.0% improvement in F1 score accuracy.

FIG. **8**D depicts a pair of plots **842** and **844** that compare training curves for a QA model with a deep coattention encoder with a mixed learning objective (solid line) and without a mixed learning objective (dotted line). Plot **842** displays the entire training curves, and plot **844** displays a close-up view of the training curves at early training stages. As indicated, the use of a mixed learning objective during training significantly increases the training rate of the QA model compared to training without the mixed learning objective.

Although illustrative embodiments have been shown and described, a wide range of modifications, changes and substitutions are contemplated in the foregoing disclosure and in some instances, some features of the embodiments may be employed without a corresponding use of other features. One of ordinary skill in the art would recognize many variations, alternatives, and modifications. Thus, the scope of the present application should be limited only by the following claims, and it is appropriate that the claims be construed broadly and in a manner consistent with the scope of the embodiments disclosed herein.

What is claimed is:

1. A computer-implemented method for training a neural network model, the method comprising:

generating, using the neural network model, a series of inferences from a first training sequence and a second training sequence;

generating a mixed learning objective from the series of inferences, wherein the generating further comprises:

determining, using a supervised learning objective, a first loss or a first reward for an inference in the series of inferences independently of other inferences in the series of inferences;

determining, using a reinforcement learning objective, a second loss or a second reward over the series of inferences by:

determining a baseline score using a scoring function, wherein the baseline score is based on baseline start and end positions of an answer span and a ground truth start and end positions of the answer span;

determining a reinforcement learning reward function based on the scoring function and the baseline score, wherein the reinforcement learning reward function is based on the ground truth start and end positions of the answer span and a start and an end positions of an inference answer span; and

determining the second loss or the second reward based on the reinforcement learning reward function; and

combining the supervised learning objective and the reinforcement learning objective into a mixed objective using the first and second loss or the first and second reward; and

updating parameters of the neural network model based on a loss or a reward in the mixed learning objective.

2. The computer-implemented method of claim **1**, wherein the updating further comprises:

determining a gradient of the mixed learning objective with respect to the parameters; and

updating the parameters based on the gradient.

3. The computer-implemented method of claim **1**, further comprising:

determining the loss or the reward of the mixed objective based on the series of inferences and a ground truth associated with the first training sequence or the second training sequence.

4. The computer-implemented method of claim **1**, wherein a differentiable objective function determines the first loss or the first reward.

5. The computer-implemented method of claim **4**, wherein the differentiable objective function is based on the start and the end positions of the inference answer span in an inference to a question in the first training sequence or the second training sequence and the start and the end positions of the ground truth answer span.

6. The computer-implemented method of claim **1**, wherein the first training sequence corresponds to a document, the second training sequence corresponds to a question, and the inference corresponds to a span of text in the document that answers the question.

7. The computer-implemented method of claim **1**, wherein the supervised learning objective is a binary evaluation objective and the reinforcement learning objective is a non-binary objective.

8. A system for training a neural network model, the system comprising:

a memory configured to store the neural network model; and

a processor configured to:

generate, using the neural network model, a series of inferences from a first training sequence and a second training sequence;

generate a mixed learning objective from the series of inferences, wherein to generate the mixed learning objective the processor is further configured to:

determine, using a supervised learning objective, a first loss or a first reward for an inference in the series of inferences independently of other inferences in the series of inferences;

determine, using a reinforcement learning objective, a second loss or a second reward over the series of inferences by:

determine a baseline score using a scoring function, wherein the baseline score is based on baseline start and end positions of an answer span and a ground truth start and end positions of the answer span;

determine a reinforcement learning reward function based on the scoring function and the baseline score, wherein the reinforcement learning reward function is based on the ground truth start and end positions of the answer span and a start and an end positions of an inference answer span; and

determine the second loss or the second reward based on the reinforcement learning reward function; and

combine the supervised learning objective and the reinforcement learning objective into a mixed objective using the first and second loss or the first and second reward; and

update parameters of the neural network model based on the mixed learning objective.

9. The system of claim **8**, wherein to update the parameters, the processor is further configured to:

determine a gradient of the mixed learning objective with respect to the parameters; and

update the parameters based on the gradient.

10. The system of claim **8**, wherein the processor is further configured to:

determine a loss and reward of the mixed objective based on the series of inferences and a ground truth associated with the first training sequence or the second training sequence.

11. The system of claim **8**, wherein a differentiable objective function determines the first loss or the first reward.

12. The system of claim **11**, wherein the differentiable objective function is based on the start and the end positions of the inference answer span in an inference to a question in the first training sequence or the second training sequence and start and end positions of the ground truth answer span.

13. The system of claim **8**, wherein the first training sequence corresponds to a document, the second training sequence corresponds to a question, and the inference corresponds to a span of text in the document that answers the question.

14. The system of claim **8**, wherein the supervised learning objective is a binary evaluation objective and the reinforcement learning objective is a non-binary objective.

15. A non-transitory computer readable medium having instructions stored thereon, that when executed by a processor cause the processor to perform operations for training a neural network model, the operations comprising:

generating, using the neural network model, a series of inferences from a training sequence;

generating a mixed learning objective from the series of inferences, wherein generating the mixed learning objective further comprises:

determining, using a supervised learning objective, a first loss or a first reward for an inference in the series of inferences independently of other inferences in the series of inferences;

determining, using a reinforcement learning objective, a second loss or a second reward over the series of inferences by:

determining a baseline score using a scoring function, wherein the baseline score is based on baseline start and end positions of an answer span and a ground truth start and end positions of the answer span;

determining a reinforcement learning reward function based on the scoring function and the baseline score, wherein the reinforcement learning reward function is based on the ground truth start and end positions of the answer span and a start and end positions of an inference answer span; and

determining the second loss or the second reward based on the reinforcement learning reward function; and

combining the supervised learning objective and the reinforcement learning objective into a mixed objective using the first and second loss or the first and second reward; and

updating parameters of the neural network model based on the mixed learning objective.

16. The non-transitory computer readable medium of claim **15**, further comprising:

determining a gradient of the mixed learning objective with respect to the parameters; and

updating the parameters based on the gradient.

17. The non-transitory computer readable medium of claim **15**, wherein the updating further comprises:

determining a gradient of the mixed learning objective with respect to the parameters; and

updating the parameters based on the gradient.

18. The non-transitory computer readable medium of claim **15**, further comprising:

determining the loss or the reward of the mixed objective based on the series of inferences and a ground truth associated with the training sequence.

19. The non-transitory computer readable medium of claim **15**, wherein the training sequence corresponds to a document or to a question, and the inference corresponds to a span of text in the document that answers the question.

20. The non-transitory computer readable medium of claim **15**, wherein the supervised learning objective is a binary evaluation objective and the reinforcement learning objective is a non-binary objective.

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